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An Intelligent Pressure Measurement Technique by Capacitance Pressure Sensor using Optimized ANN

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***Abstract*—Design of an intelligent pressure measurement technique by Capacitance Pressure Sensor (CPS) using an optimized Artificial Neural Network (ANN) is reported in this paper. The objectives of the present work are: (i) to extend the linearity range of measurement to 100% of input range, (ii) make the measurement technique adaptive to variation in physical parameters of diaphragm in CPS like, elasticity modulus and thickness, permittivity of dielectric constant, and temperature, and (iii) to achieve objectives (i) and (ii) using an optimized neural network. A suitable optimal ANN is added, replacing the conventional calibration circuit, in cascade to data conversion unit. The proposed measurement technique is tested considering variations in physical parameters of CPS, and temperature. These parametric variations are considered within the specified ranges. Results show that the proposed intelligent technique has fulfilled the objectives.**

***Index Terms* — Artificial Neural Network, Optimization, Capacitive Pressure Sensor, Non linear estimation, Sensor modeling, Temperature compensation.**

I. Introduction

A pressure sensor measures pressure, typically of gases or liquids. Pressure is an expression of the force required to stop a fluid from expanding, and is usually stated in terms of force per unit area. A pressure sensor acts as a transducer. It generates a signal as a function of the input pressure applied. Pressure sensors are used for control and monitoring in thousands of applications. These applications demand that the sensors should be of low cost, but have high linearity, sensitivity and resolution and can be produced in mass. Many sensors are used for this purpose; Capacitance Pressure Sensors (CPS) finds a very wide application because of its high sensitivity and ruggedness. However, the problem of offset, high non-linear response characteristics and, dependence of output on the thickness and Modulus of Elasticity (E) of diaphragm in a CPS have restricted its use and further imposes some difficulties.

Literature survey suggests that in [1], compensation of CPS nonlinearities is done using neurofuzzy algorithms. In [2], Calibration of CPS is discussed using circuits. In [3], calibration of CPS is done using least square support vector regression, and for temperature compensation one more CPS is used. In [4], extension of linearity is achieved using Hermite neural network algorithm. In [5], Chebyshev neural network algorithm is used for extension of linearity. In [6], non linearity of CPS is compensated by using Hybrid Genetic Algorithm-Radial Basis Function neural network (HGA-RBF). In [7], calibration of CPS is done using DSP algorithms. In [8], FLANN algorithm is used for calibrations of CPS. In [9], Laguerre neural network is used for calibration of CPS. In [10], Calibration of CPS is achieved using ANN. Adaptation to physical properties of diaphragm, and temperature is also discussed. In [11], relation between diaphragm properties and CPS output is discussed. In [12], effect of dielectric properties on CPS output is discussed. In [13], effect of temperature on CPS output is discussed.

An intelligent pressure measurement technique is proposed as an improvement to the earlier reported works [10]. The technique is designed to obtain full scale linearity of input range and makes the output adaptive to variations in physical properties of diaphragm, dielectric constant, and temperature, all using the optimized ANN model.

The paper is organised as follows: after introduction in Section-I, a brief description on CPS is given in Section-II. The output of the CPS is capacitance; a brief note on data conversion i.e. timer circuit and frequency to voltage (f-V) converter is given in Section-III. Section-IV deals with the problem statement followed by proposed solution in Section-V. Results and analysis is given in Section-VI. Finally, conclusion and future scope are discussed in Section VII.

II. Capacitance pressure sensor

CPS uses a thin diaphragm, usually metal or metal-coated quartz, as one plate of a capacitor. The diaphragm is exposed to the process pressure on one side. Changes in pressure cause it to deflect and change the capacitance which is proportional to the applied pressure. Fig 1 shows the model of the CPS [14]-[17].

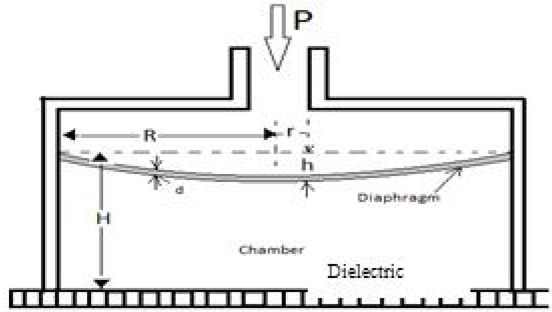

Figure 1. Capacitance Pressure Sensor

Assuming a circular diaphragm restrained around its circumference, the elastic deflection ‘h’ at distance ‘r’ from

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the centre of the diaphragm under pressure ‘P’ is given by

$$h = \frac{P\Psi(1-q^2)^2}{\Phi} \text{ m} \quad (1)$$

Where

$\Psi = 3(1-\rho^2)R^4$

$\Phi = 16\,E\,d^3$

$q = r / R$

ρ - Poisson ratio

E - Modulus of Elasticity

ϵ_r - Permittivity of dielectric

Variation of Modulus of Elasticity with temperature [11], [12], [18] can be given by (2)

$$E(t) = E(25) * \left[1 + \left[\frac{t}{200 * \left[\ln\left(\frac{t}{1100}\right) \right]} \right] \right] \text{Pa} \quad (2)$$

where

E (t) = Modulus of Elasticity at temperature t°C

E (25) =Modulus of Elasticity at temperature 25°C

t = Temperature in °C

Using (2) in (1), the equation for the deformation caused due to the pressure applied can be found under different temperatures. The effective capacitance of the chamber may be expressed as

$$C = \int_0^R \frac{2\pi r}{H-h}\, dr \text{ F} \quad (3)$$

By using the above equations (1) and (3), the capacitance can be found as

$$C = \frac{\pi R^2 \epsilon_0 \epsilon_r}{H} \left(\sqrt{\frac{P\Psi}{\Phi H}} \right) \tanh^{-1}\left(\frac{P\Psi}{\Phi H} \right) \text{ F} \quad (4)$$

Capacitance is also a function of temperature [13], [19], which can be given by the (5)

$$C(t) = C(t_o) * (1 + \alpha(t - t_o) + \beta(t - t_o)^2) \text{ F} \quad (5)$$

where

C (t) = capacitance at temperature t°C

C (t_o) = capacitance at temperature t_o °C

α, β = constants

Using (4) and (5) the effective capacitance change for the pressure applied for different values of temperature can be found.

III. Data Conversion Unit

The block diagram representation of the proposed instrument is given in Fig 2.

Timer circuit consist of a 555 IC connected in astable mode [20]. This circuit generates a train of pulses whose frequency is given by.

$$f = \frac{1}{\ln(2) * (R_1 + 2R_2) * C} \text{ Hz} \quad (6)$$

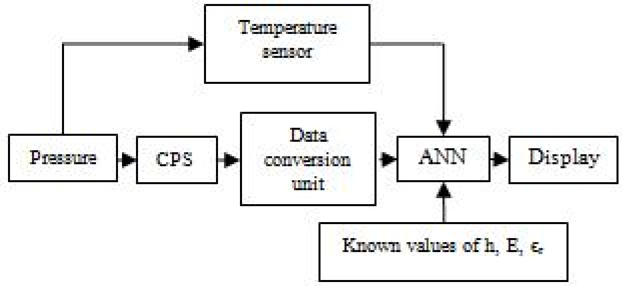

Figure 2. Block diagram

From (6), it’s clear that the frequency of the timer depends on the capacitance (CPS). Now the input Pressure applied on the CPS is converted to frequency. This frequency is further converted to voltage.

Frequency to voltage converter (f-V) [21], is a circuit which converts the given frequency into voltage and is given by

$$V_{out} = (V_s * C1 * R1) * f \text{ V} \quad (7)$$

IV. Problem Statement

In this section, characteristics of CPS are simulated to understand the difficulties associated with the available measurement technique. For this purpose, simulation is carried out with three different elasticity modulus of diaphragm. These are E_1 = 70 GPa, E_2 = 10 GPa, and E_3 = 130 GPa. Further, three different diaphragm thicknesses are considered. These are h_1 = 0.5mm, h_2 = 0.52mm, and h_3 = 0.54mm. Three different dielectric constants as $õ_{r1}$ = 30, $õ_{r2}$ = 60, and $õ_{r3}$ = 90 are chosen. Different temperatures, like t_1 = 25°C, t_2 = 50° C, and t_3 = 75°C are used to find the output capacitance of CPS with respect to various values of input pressure considering a particular elasticity modulus for diaphragm, thickness of diaphragm, permittivity of dielectric constant, and temperature. These output pressure data are used as input of data conversion unit and output voltages are generated.

The MATLAB environment is used of and the following characteristics are simulated.

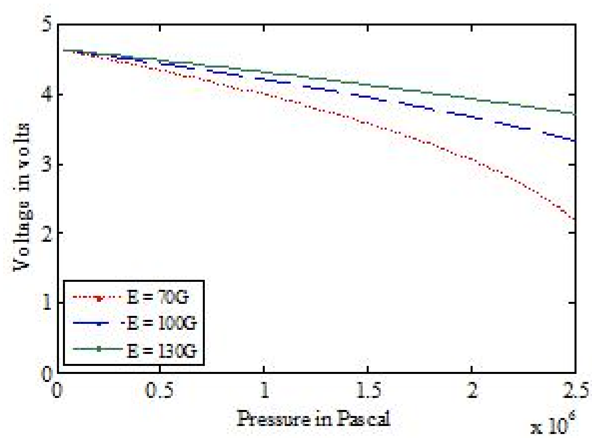

Figure 3. Input pressure Vs voltage outputs for variations of pressure and elasticity modulus of diaphragm with diaphragm thickness of 0.5mm, dielectric constant of 30, and temperature of 25°C

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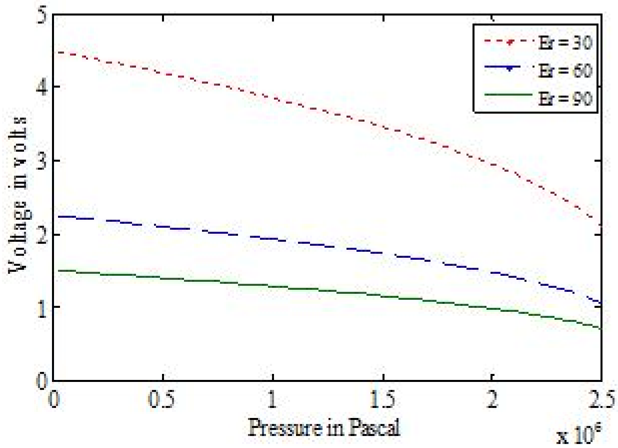

Figure 4. Input pressure Vs voltage outputs for variation of pressure and dielectric constants with temperature of 25°C, elasticity modulus of diaphragm of 70GPa, and diaphragm thickness of 0.54mm

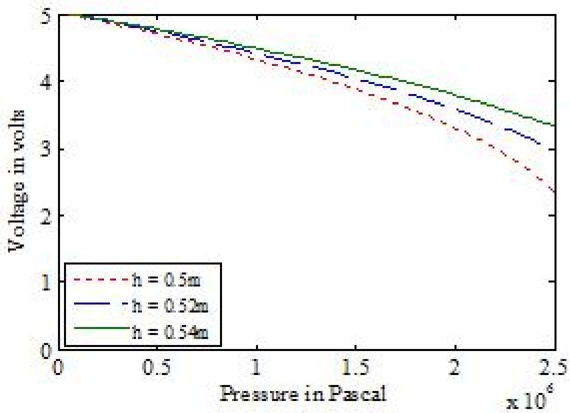

Figure 5. Input pressure Vs voltage outputs for variation of pressure and diaphragm thickness with, temperature of 25°C, modulus of elasticity of diaphragm of 100 GPa, and dielectric constant of 30

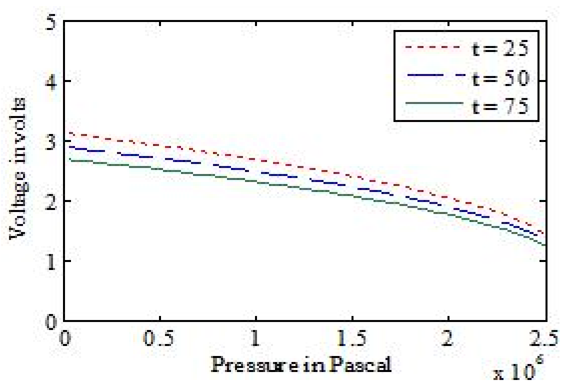

Figure 6. Input pressure Vs voltage outputs for variation of pressure and temperature with modulus of elasticity of diaphragm of 100 GPa, dielectric constant of 30, and diaphragm thickness of 0.5mm

Fig.3, Fig.4, Fig.5, and Fig.6 show the variation of voltage with changes in input pressure considering different values of elasticity modulus of diaphragm, diaphragm thickness, dielectric constant, and temperature.

It has been observed from the above graphs (Fig.3, Fig.4, Fig.5, and Fig.6) that the relation between input pressure and voltage output of data converter unit is non-linear. Datasheet of CPS suggests that the input range of 10% to 75% of full scale is used in practice as linear range. The output voltage also varies with the changes in elasticity modulus of diaphragm, diaphragm thickness, dielectric constant, and temperature. These are the reasons which have made the user to go for calibration techniques using some circuits. These conventional calibration techniques have drawbacks that these are time consuming and need to be calibrated whenever there is any change in elasticity modulus of diaphragm, diaphragm thickness, permittivity of dielectric constant, and temperature. Further, the use is restricted only to a portion of full scale.

To overcome these drawbacks, this paper proposes to design a pressure measurement technique incorporating intelligence to produce full scale linear output and to make the system adaptive to variations in elasticity modulus of diaphragm, diaphragm thickness, permittivity of dielectric constant, and temperature, using an optimized artificial neural network.

V. Problem solution

The drawbacks discussed in the earlier section are overcomed by adding an optimized suitable ANN model, replacing the conventional calibration circuit, in cascade with data converter unit. This model is designed using the neural network toolbox of MATLAB.

The first step in developing a neural network is to create a database for its training, testing, and validation. The output voltage of data conversion unit for a particular pressure, physical parameters of CPS, like, elastic modulus of diaphragm, diaphragm thickness, permittivity of dielectric constant, and temperate, is stored as a row of input data matrix. Various such combinations of input pressure, elasticity modulus of diaphragm, diaphragm thickness, permittivity of dielectric constant, temperature, and their corresponding voltages at the output of data conversion unit are used to form the other rows of input data matrix. The output matrix is the target matrix consisting of data having a linear relation with the pressure and adaptive to variations in elastic modulus of diaphragm, diaphragm thickness, permittivity of dielectric constant, and temperature, as shown in Fig.7.

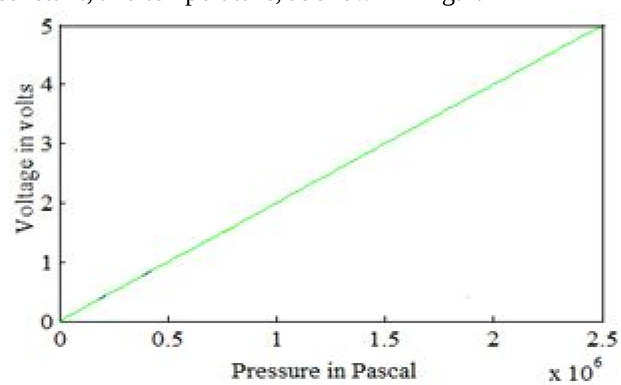

Figure 7. Target graph

Schemed trained by algorithm

AL - 1: linear trained Levenberg-Marquardt Algorithm (LMA)

AL - 2: linear trained Guass Newton Algorithm (GNA)

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AL – 3: linear trained Artificial Bee Colony (ABC)

AL – 4: Back Propagation neural network trained by Ant Colony Optimization (BP_ACO)

AL – 5: Radial Basis Function (RBF) trained by Ant Colony Optimization (RBF_ACO)

TABLE 1. COMPARISON OF DIFFERENT ANN MODELS

Layers		AL - 1	AL - 2	AL - 3	AL - 4	AL - 5
1	MSE	5.6E-1	6.2E-1	0.6E-1	8.5E-2	4.2E-2
	R	0.623	0.811	0.890	0.921	0.948
2	MSE	2.6E-2	1.2E-2	6.8E-3	5.7E-4	2.1E-4
	R	0.886	0.936	0.990	0.996	0.999
3	MSE	8.2E-4	2.1E-4	4.8E-5	6.7E-5	7.8E-6
	R	0.986	0.991	0.999	0.999	0.9996
4	MSE	3.2E-6	0.2E-6	4.8E-7	2.2E-7	3.1E-8
	R	0.9997	0.9999	0.99993	0.99994	0.99998
5	MSE	1.1E-9	2.1E-9	6.7E-10	4.2E-10	1.1E-10
	R	0.99999	0.99999	0.99999	0.99999	0.99999

The process of finding the weights to achieve the desired output is called training. The optimized ANN is found by considering five different algorithms with varying number of hidden layer. Mean Squared Error (MSE) is the average squared difference between outputs and targets. Lower values of MSE are better. Zero means no error. Regression (R) measures the correlation between output and target. Regression equal to one means a close relationship and zero means a random relationship.

Five different schemes and algorithms are used to find the optimized ANN. These are LMA [21], [22], GNA [22], [23], ABC [24], [25], BP_ACO [26]-[29], and RBF_ACO [29]-[32]. Training of ANN is first done assuming only one hidden layer. MSE and R values are noted. Hidden layer is increased to 2 and training is repeated. This process is continued up to 5 hidden layers. In all cases MSE and R are noted and are shown in table-1. Mesh of MSE and R corresponding to different algorithms and hidden layers are shown in Fig.8 and Fig.9. From table-1, Fig.8 and Fig.9, it is very clear that ANN model with RBF scheme and trained by ACO yields most optimized network for a desired MSE as threshold. RBF trained by ACO with 2 hidden layers is considered as the most optimized ANN for desired accuracy of result.

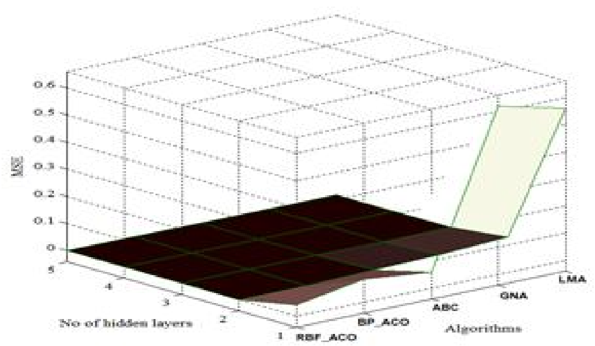

Figure 8. Mesh showing the MSE corresponding to different ANN models

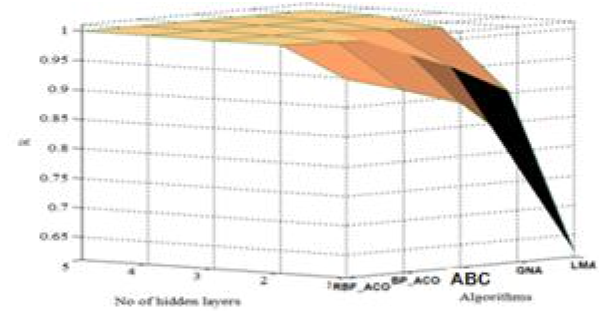

Figure 9. Mesh showing the Regression (R) corresponding to different ANN models

The network is trained, validated, and tested with the details mentioned above. Table-2 summarizes the various parameters of the optimized neural network model.

TABLE II. SUMMARY OF OPTIMIZED ANN MODEL

<table>
<tr><td colspan="7">PARAMETERS OF THE OPTIMIZED NEURAL NETWORKS MODEL</td></tr>
<tr><td colspan="3" rowspan="3">Database</td><td colspan="2">Training base</td><td colspan="2">84</td></tr>
<tr><td colspan="2">Validation base</td><td colspan="2">28</td></tr>
<tr><td colspan="2">Test base</td><td colspan="2">28</td></tr>
<tr><td colspan="3" rowspan="2">No of neurons in</td><td colspan="2">1st layer</td><td colspan="2">7</td></tr>
<tr><td colspan="2">2nd layer</td><td colspan="2">8</td></tr>
<tr><td colspan="3" rowspan="3">Transfer function of</td><td colspan="2">1st layer</td><td colspan="2">Tansig</td></tr>
<tr><td colspan="2">2ndd layer</td><td colspan="2">Tansig</td></tr>
<tr><td colspan="2">Output layer</td><td colspan="2">Linear</td></tr>
<tr><td rowspan="3">Input</td><td></td><td>Pressure</td><td>E</td><td>h</td><td>ϵ_r</td><td>Temp</td></tr>
<tr><td>min</td><td>0.0 Pa</td><td>70 GPa</td><td>0.50 mm</td><td>30</td><td>25°C</td></tr>
<tr><td>max</td><td>2.5 MPa</td><td>130 Gpa</td><td>0.54 mm</td><td>90</td><td>75°C</td></tr>
</table>

VI. RESULTS AND ANALYSIS

The proposed optimized ANN is trained, validated, and tested with the simulated data. Once the training is over, the system with CPS along with other modules, as shown in Fig 2, is subjected to various test inputs corresponding to different pressures with a particular elastic modulus of diaphragm, diaphragm thickness, permittivity of dielectric constant, and temperature, all within the specified range. For testing purposes, various parameters are chosen within the specified ranges, the range of pressure is considered from 0 to 2.5×10^6Pa, the range of E is from 70 to 130 GPa, the range of h is from 0.50 to 0.54 mm, the range of $\tilde{o}_r$ is from 30 to 90, and temperature is from 25 to 75°C. The outputs of the proposed technique with ANN are noted corresponding to various input pressures with different values of E, h, $\tilde{o}_r$, and t. The results are listed in table-3. Further, the input-output result is plotted and is shown in Fig 10. The response graph in Fig. 10 is matching the target graph as shown in Fig 8.

It is evident from Fig 10, and table-3, that the proposed measurement technique has incorporated intelligence. It has increased the linearity range of the CPS to 100% of input range. Also, the output is made adaptive to variations in the elasticity modulus of diaphragm, diaphragm thickness, permittivity of dielectric constant, and temperature. Thus, if

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TABLE III. SHOWS THE RESULTS OF PROPOSED TECHNIQUE FOR VARIOUS INPUT CONDITIONS

AP in 10^6 Pa	E in GPa	h in mm	ϵ_r	t in °C	DCO in V	ANN o/p in V	MP in 10^6 Pa
0.5	70	0.54	30	25	4.99	1.0	0.5
0.5	75	0.53	35	30	4.86	1.0	0.5
0.5	80	0.52	40	35	4.19	1.0	0.5
1.0	85	0.51	45	40	3.45	2.0	1.0
1.0	90	0.50	50	45	3.06	2.0	1.0
1.0	95	0.50	55	50	2.76	2.0	1.0
1.5	100	0.51	60	55	2.38	3.0	1.5
1.5	105	0.52	65	60	2.20	3.0	1.5
1.5	110	0.53	70	65	2.05	3.0	1.5
2.0	115	0.54	75	70	1.83	4.0	2.0
2.0	120	0.54	80	75	1.71	4.0	2.0
2.0	125	0.53	85	70	1.63	4.0	2.0
2.5	130	0.52	90	65	1.48	5.0	2.5
2.5	75	0.51	85	60	1.55	5.0	2.5
2.5	80	0.50	80	55	1.25	5.0	2.5

AP- Actual pressure
MP- Measured pressure
DCO- Data Conversion circuit output

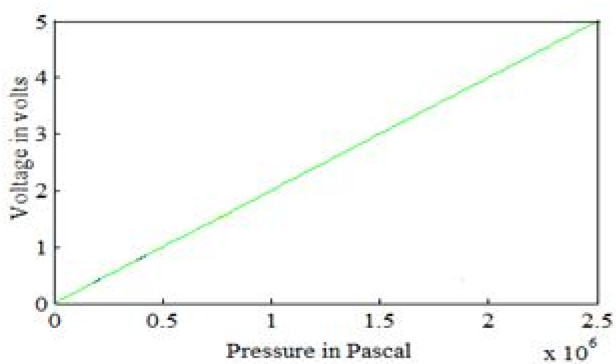

Fig.10. Response of the system for test inputs

the diaphragm is replaced, and/or dielectric is changed, the proposed system does not require any repeated calibration. Similarly, if there is a change in environment conditions, like change in temperature, the system does not require any further calibration to give the accurate reading.

Five different schemes and algorithms are compared to find the optimized ANN. An ANN model with less number of hidden layers for performing same task is considered as optimal. An ANN model with RBF trained by ACO is found to perform the task with 2 hidden layers and is termed as optimized. Simulation results show that the objectives have been achieved quite satisfactorily.

VII. CONCLUSIONS AND FUTURE SCOPE

Available reported works have discussed different techniques for calibration of pressure measurement, but these are not adaptive of variations in physical parameters, like elasticity modulus and thickness of diaphragm of CPS, permittivity of dielectric constant, and environmental conditions like temperature. Hence, repeated calibration is required for any change of physical parameters of CPS, permittivity of dielectric constant, and temperature. Sometime the calibration circuit may itself be replaced which is a time consuming and tedious procedure. Further, most of the reported works have not utilized the full scale of measurement. In comparison to these, the proposed measurement technique achieves linear input output characteristic for full scale input range and makes the output adaptive to variations in physical parameters of CPS, dielectric constant, and temperature. All these have been achieved by using an optimal ANN. This is in contrast to an arbitrary ANN considered in most of the earlier reported works.

Validation of the proposed technique by practical data and implementation on chip will be carried out as future works.

REFERENCES

[1] Jun Li, Feng Zhao, "Nonlinear Inverse Modeling of Sensor Characteristics Based on Compensatory Neurofuzzy Systems", *Proc. 1st International Symposium on System and Control in Aerospace and Astronautics*, Harbin, China, January 2006.

[2] Yi Leng, Genbao Zhao, Qingxia Li, Chunyu Sun, Sheng Li, "A High Accuracy Signal Conditioning Method and Sensor Calibration System for Wireless Sensor in Automotive Tire Pressure Monitoring System", *Proc. International Conference on Wireless Communications, Networking and Mobile Computing*, Shangai, China, September 2007.

[3] Xiaoh Wang, "Non-linearity Estimation and Temperature Compensation of Capacitor Pressure Sensor Using Least Square Support Vector Regression", *Proc. International Symposium on Knowledge Acquisition and Modeling Workshop*, Beijing, China, December 2008.

[4] Jagdish C. Patra, Cedric Bornand, Goutam Chakraborty, "Hermite Neural Network-based Intelligent Sensors for Harsh Environments", *Proc. International Conference on Neural Networks*, Georgia, USA, June 2009.

[5] Jagadish C Patra, Cedric Bornand, "Development of Chebyshev Neural Network-based Smart Sensors for Noisy Harsh Environment", *Proc. World Congress on Computational Intelligence, Barcelona*, Spain, July, 2010.

[6] Zhiqiang Wang, Ping Chen, Mingbo Zhao, "Approaches to Non-Linearity Compensation of Pressure Transducer Based on HGA-RBFNN", *Proc. 8th World Congress on Intelligent Control and Automation*, Jinan, China, July 2010.

[7] Yang Chuan, Li Chen, "The Intelligent Pressure Sensor System Based on DSP", *Proc. 3rd International Conference on Advanced Computer Theory and Engineering*, Chengudu, China, August 2010.

[8] Jiaoying Huang, Haiwen Yuan, Yong Cui, Zhiqiang Zheng, "Nonintrusive Pressure Measurement With Capacitance Method Based on FLANN", *IEEE Transactions on Instrumentation and Measurement*, vol. 59, no. 11, pp. 2914-2920, November 2010.

[9] Jagadish Chandra Patra, Pramod Kumar Meher, Goutam Chakraborty, "Development of Laguerre Neural-Network-

DOI: 01.IJEPE.4.1.1076

Based Intelligent Sensors for Wireless Sensor Networks", *IEEE Transactions on Instrumentation and Measurement*, vol. 60, no. 3, March 2011.

[10] Santhosh K V, B K Roy, "An Improved Smart Pressure Measuring Technique", *Proc. The International Joint Colloquiums on Computer Electronics Electrical Mechanical and Civil*, Muvatupuzha, India, 20-21 September 2011.

[11] Norhayati Soin, Burhanuddin Yeop Majids, "An Analytical Study on Diaphragm Behavior for Micro-Machined Capacitance Pressure Sensor", *Proc. International Conference on Semiconductor Electronics*, Penang, Malaysia, December, 2002.

[12] Zongyang Zhang, Zhimin Wan, Chaojun Liu, Gang Cao, Yun Lu, Sheng Liu, "Effects of Adhesive Material on the Output Characteristics of Pressure Sensor", *Proc. 11th International Conference on Electronic Packaging Technology and High Density Packaging*, Shanghai, China, August, 2011.

[13] Cui Chun sheng, Ma Tie Hua, "The research of temperature compensation Technology and High-temperature Pressure Sensor", *Proc. International Conference on Electronic & Mechanical Engineering and Information Technology*, Harbin, China, August, 2011.

[14] Neubert, H. K. P, *Instrument Transducers: an Introduction to their Performance and Design*, Clarendon Press, Oxford 1975.

[15] Lyons, J. L., *The Designer's Handbook of PI-Pressure-Sensing Devices*, Van Nostrand Reinhold, New York, 1980.

[16] Bela G Liptak, *Instrument Engineers' Handbook: Process Measurement and Analysis*, 4th Edition, CRC Press, June 2003.

[17] E.O. Doebelin, *Measurement Systems - Application and Design*, Tata McGraw Hill publishing company, 5th edition, 2003.

[18] *AS4100 Fire Provision* "ANSI Standards", *Federal Register* vol. 74, no. 69, April 2009.

[19] N Krotkov and M D Klionskii, "Evaluation of the temperature characteristic of reference capacitors". Springer. pp 52-56 September 1996.

[20] *LM555 Datasheet*, National Semiconductor Cooperation, 2001.

[21] *LM331 Datasheet*, National Semiconductor Corporation, 2006.

[22] Fernando Morgado Dias, Ana Antunes1, José Vieira, Alexandre Manuel Mota, "Implementing The Levenberg-Marquardt Algorithm On-line: a sliding window approach with early stopping". *International Conference IFAC*, USA, 2004.

[23] Björck A, *Numerical methods for least squares problems*, SIAM Publications, Philadelphia. ISBN 0-89871-360-9, 1996.

[24] Fletcher, Roger, *Practical methods of optimization*, 2nd Edition, John Wiley & Sons, New York. ISBN 978-0-471-91547-8, 1987.

[25] D. Karaboga, *An idea based on honey bee swarm for numerical optimization*, Technical report-tr06, Erciyes university, engineering faculty, computer engineering department 2005.

[26] R. Venkata Rao, *Multi-objective optimization of multi-pass milling process parameters using artificial bee colony algorithm. Artificial Intelligence in Manufacturing*, Nova Science Publishers, USA, 2011.

[27] Jeng-Bin Li, Yun-Kung Chung, "A Novel Back propagation Neural Network Training Algorithm Designed by an Ant Colony Optimization", *IEEE/PES Transmission and Distribution Conference & Exhibition*: Asia and Pacific Dalian, China 2005

[28] L. Bianchi, L.M. Gambardella, M.Dorigo, "An ant colony optimization approach to the probabilistic travelling salesman problem", *Proc. of PPSN-VII, Seventh Inter17 national Conference on Parallel Problem Solving from Nature,* Springer Verlag, Berlin, Germany, 2002

[29] Stuart Russell and Peter Norvig, *Artificial Intelligence A Modern Approach*, 3rd Edition, Prentice Hall New York, 2009.

[30] T Poggio, F Girosi, "Networks for approximation and learning," *Proc. IEEE 78(9*), pp. 1484-1487, 1990.

[31] Park J, Sandberg J W, "Universal Approach Using Radial Basis Function Network, Neural Computation", Vol 3, pp. 246-257, 1991

[32] Paul Yee V and Simon Haykin, *Regularized Radial Basis Function Networks: Theory and Applications*, John Wiley, 2001.

DOI: 01.IJEPE.4.1.1076